DEVELOPING A HYBRID HIDDEN MARKOV MODEL USING FUSION OF ARMA MODEL AND ARTIFICIAL NEURAL NETWORK FOR CRUDE OIL PRICE FORECASTING

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DEDICATION

I dedicated this thesis to my dear father and my loving mother for their unwavering support, advice, encouragement, and prayers which guided me towards this achievement, I am indeed proud of you.

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ABSTRACT

Crude oil price forecasting is an important component of sustainable development of many countries as crude oil is an unavoidable product that exist on earth. Crude oil price forecasting plays a very vital role in economic development of many countries in the world today. Any fluctuation in crude oil price tremendously affects many economies in terms of budget and expenditure. In view of this, it is of great concern by economists and financial analysts to forecast such a vital commodity. However, Hidden Markov Model, ARMA Model and Artificial Neural Network has many drawbacks in forecasting such as linear limitations of ARMA model which is in contrast to the financial time series which are often nonlinear, ANN is very weak in terms of out-sample forecast and it has very tedious process of implementation, HMM is very weak in an in-sample forecast and has issue of a large number of unstructured parameters. In view of this drawbacks of these three models (ANN, ARMA and HMM), we developed an efficient Hybrid Hidden Markov Model using fusion of ARMA Model and Artificial Neural Network for crude oil price forecasting, MATLAB was employed to develop the four models (Hybrid HMM, HMM, ARMA and ANN). The models were evaluated using three different evaluation techniques which are Mean Absolute Percentage Error (MAPE), Absolute Error (AE) and Root Mean Square Error (RMSE). The findings showed that Hybrid Hidden Markov Model was found to provide more accurate crude oil price forecast than the other three models in which. The results of this study indicate that Hybrid Hidden Markov Model using fusion of ARMA and ANN is a potentially promising model for crude oil price forecasting.

ABSTRAK

Ramalan harga minyak mentah merupakan komponen penting dalam pembangunan mampan banyak negara kerana minyak mentah adalah produk yang tidak dapat dielakkan yang ada di bumi. Peramalan harga minyak mentah memainkan peranan yang sangat penting dalam pembangunan ekonomi banyak negara di dunia hari ini. Mana-mana turun naik harga minyak mentah amat menjejaskan banyak ekonomi dari segi anggaran dan perbelanjaan. Memandangkan ini, ia sangat membimbangkan oleh ahli ekonomi dan penganalisis kewangan untuk meramalkan komoditi penting itu. Walau bagaimanapun, Model Markov Tersembunyi, Model ARMA dan Rangkaian Neural Buatan mempunyai banyak kelemahan dalam peramalan seperti batasan linear model ARMA yang berbeza dengan siri masa kewangan yang sering tidak linear, ANN sangat lemah dari ramalan luar sampel dan ia mempunyai proses pelaksanaan yang sangat membosankan, HMM sangat lemah dalam ramalan dalam sampel dan mempunyai sejumlah besar parameter tak berstruktur. Memandangkan kelemahan ketiga model ini (ANN, ARMA dan HMM), kami membangunkan Model Markov Tersembunyi Hibrid yang efisien menggunakan gabungan Model ARMA dan Rangkaian Neural Buatan untuk ramalan harga minyak mentah, MATLAB telah digunakan untuk membangunkan empat model (Hybrid HMM, HMM, ARMA dan ANN). Model-model ini dinilai dengan menggunakan tiga teknik penilaian yang berbeza iaitu Ralat Peratusan Maksimum Mutlak (MAPE), Ralat Mutlak (AE) dan Kesalahan Ruas Panjang Root (RMSE). Penemuan menunjukkan bahawa Model Markov Tersembunyi Hibrid didapati memberikan ramalan harga minyak mentah yang lebih tepat daripada tiga model lain di mana. Keputusan kajian ini menunjukkan bahawa Model Markov Tersembunyi Hibrid menggunakan gabungan ARMA dan ANN adalah model berpotensi menjanjikan untuk ramalan harga minyak mentah.

TABLE OF CONTENT

CHAPTER 2 LITERATURE REVIEW

CHAPTER 3 METHODOLOGY

CHAPTER 4 DATA ANALYSIS

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

1.1 Introduction

Crude oil is made up of a combination of many hydrocarbons and organic compounds (Walters, 2017), most of them are alkenes and minor amount pf aromatics. Crude oil varies in color from nearly colorless to tar black, and in viscosity from close to that of water to almost solid. There are however, more than 350 categories of crude oil produced around the globe (Faramawy *et al.*, 2016). Two of the most important characteristics are density and sulfur content. High-quality crude oil is characterized by low density (light) and low sulfur content (sweet) and are typically more expensive than their heavy and sour counterparts. However, the region with substantial amount of oil is Middle East with 51% of the total oil around the world, then South America and Central America with 16% oil reserve, Europe in exception of Eastern Europe and Russia has only 1% reserve of world oil deposit (Guoqi *et al.*, 2015). On the country level the biggest oil reserves belong to Saudi Arabia and Venezuela together owning around one third of world oil. Among ten countries with biggest reserves are also Canada, Iraq, Iran, Kuwait, UAE, Russia, Libya and Nigeria. Eighteen (18) countries in the world own reserves of more than 10 bb and 51, including Denmark, less than 1 bb. Worldwide there are more than four thousand oil fields, most of them are relatively small with production up to 20 thousand b/d. Gigantic oil fields have daily producing capacity of more than 0.1 mb/d or reserves more than 500 mb (Colgan, 2014).

However, significant fluctuations in crude oil prices have caused considerable interest among crude oil marketers and controllers. The reasons for this is that the volatility of crude oil price has a significant effect on the economy of many countries

(Walters *et al.*, 2017). Theories of both investments under uncertainty and real options predict that uncertainty about oil prices can reduce current investment. Also, the volatility is a crucial input in pricing options and a significant determinant of the value at risk. Therefore, the modeling and forecasting of crude oil prices are of considerable importance for economic development.

Forecasting of crude oil price is among the crutial roles that financial analysts and economists plays for economic growth and development of many countries. (Faramawy *et al.*, 2016). By its nature, crude oil price is mostly complex, non-linear and volatile, the rate of price fluctuations in such series depends on many factors, such as political, economic and social. Therefore, developing models of forecasting requires an iterative process of knowledge discovery and system improvement through data mining, knowledge engineering, theoretical and data-driven modeling, and also trial and error testing. Crude oil has become an essential part of the global economy. Any fluctuation in crude oil prices influences our personal and corporate financial lives, and the economic health of a country. An 'intelligent' prediction model for crude oil price forecasting would be highly desirable and of broader interest.

Therefore, in this thesis, new hybrid Hidden Markov Model (HMM) using fusion of Autoregressive Moving Average (ARMA) and Artificial Neural Network (ANN) models was developed to forecast crude oil price and provides a possible price range of crude oil.

1.2 Background of the Study

Crude oil is a naturally occurring and flammable liquid found in rock formations in the earth. It contains various gasses and organic compounds (Mokhatab *et al.*, 2018).

The main characteristics of crude oil are generally classified according to its sulphur content and its density which the petroleum industry measured by its American Petroleum Institute (API) gravity. Crude oil is considered light if it has low density with API gravity less than about 40. Heavy crude oil has high density with API gravity 20 or less. In other words, the more the API gravity, the lower the density. Brent crude is important benchmark crude which has an API gravity of 38 to 39. Crude oil may be referred to as sweet if it contains less than 0.5% sulphur or sour if it contains large amounts of sulphur. The most preferable crude oil for production is sweet crude because it is more valuable and has enough ingredients (Huang *et al.*, 2016).

Moreover, in the crude oil international market there are two bodies which are West Texas Intermediate (WTI) and Europe Brent (EB). The first one (WTI) is the base grade traded, as ‘light sweet crude, which is listed on the New York Mercantile Exchange (NYMEX) for delivery at Cushing, Oklahoma. While the second one (EB) is traded on London’s International Petroleum Exchange (IPE) for delivery at Sullom Voe and upcouce, one of the grades acceptable for delivery of the NYMEX contract (Etiope, 2017).

Similarly, crude oil has many features such as API gravity, sulphur content etc, the vast majority of oil is not traded on an exchange but an over the counter basis. Some other essential benchmarks include Dubai, Tapis (Malaysia), Minas (Indonesia) and Organization of the Petroleum Exporting Countries (OPEC) basket.

Moreover, ample studies are addressing the accuracy of crude oil volatility modeling and forecasting. These include a novel hybrid method for crude oil price forecasting (Zhang *et al.*, 2015), a deep learning ensemble approach for crude oil price forecasting (Zhao *et al.*, 2017), a novel decomposition ensemble model with extended extreme learning machine for crude oil price forecasting (Yu *et al.*, 2016), Forecasting energy market indices with recurrent neural networks: Case study of crude oil price fluctuations (Wang *et al.*, 2016), A non-iterative decomposition-ensemble learning paradigm using RVFL network for crude oil price forecasting (Tang *et al.*, 2018) and etc.

However, some of the models that have gained enormous popularity in many areas and forecasting research practice are ARMA model, Artificial Neural Network and Hidden Markov model, these models have been used widely in forecasting by many researchers, such as; Lin, Xiao, and Li, (2020) they forecasted crude oil price volatility via a HM-EGARCH model, Deng, Xiang, Nan, Tian, and Sun, (2019) developed a hybrid model of dynamic time wrapping and hidden Markov model for forecasting and trading in crude oil market, Zhu, Ching, Elliott, Siu, and Zhang, (2017). Developed a Hidden Markov models with threshold effects and their applications to oil price forecasting, Mostafa, and El-Masry, (2016). Conducted a research on oil price forecasting using gene expression programming and artificial neural networks, Kristjanpoller, and Minutolo, (2016) conducted a research on forecasting volatility of oil price using an artificial neural network-GARCH model, Ramyar and Kianfar, (2019) forecasted crude oil prices in which they compared an artificial neural networks and vector autoregressive models, Guo, (2019) conducted a research on oil price forecast using deep learning and ARIMA, Rezaeyan, and Taghizadeh, (2018) Modeled and Forecasted crude oil price with an Autoregressive Integrated Moving Average (ARIMA) Model. However, all the above models developed by other researchers have their own shortcoming in terms of accuracy in forecasting (Qin, and Cheng., 2017), (Tian, Niu, and He., 2017), (Singh and Dwivedi., 2018), these reasons motivate us to develop hybrid HMM forecasting model and compare it accuracy with the three model (HMM, ARMA and ANN).

1.3 Problem Statement

Accurate forecasting constitutes a fascinating challenge for theoretical researchers and practitioners. One of the largest domains that share this problem is economy or more specifically financial markets. Predicting a financial series, as a stock market index or an exchange rate, remains however a very challenging task. However, there have been many forecasting models used by researchers such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Autoregressive Conditional Heteroskedasticity (ARCH), Simple Moving Average (SMA), and Exponential Smoothing (SES), Vector Autoregression (VAR), Vector Autoregression Moving-Average with Exogenous Regressors (VARMAX), Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors (SARIMAX), of all the above mentioned model, the most widely used models are employed in this research work which are Autoregressive Moving Average (ARMA), Artificial Neural Network (ANN) and Hidden Markov Model.

For more than four decades, Box and Jenkins' Auto-Regressive Integrated Moving Average (ARIMA) model (Box & Jenkins, 1970) has been widely used for time series forecasting. However, some problems arise when forecasting financial time series with ARIMA models, first is the characteristic linear limitation of ARIMA models, in contrast to real-word financial time series, which are often nonlinear (Adebiyi *et al.,* 2014), (Lasheras *et al.,* 2015). Second is the robustness limitation of ARIMA models, the ARIMA model selection procedure depends greatly on the competence and experience of the researchers to yield desired results. Unfortunately, choice among competing models can be arbitrated by similar estimated correlation patterns and may frequently reach inappropriate forecasting results (Dickey, 2015), (Katris *et al.*, 2015).

Similarly, another forecasting model that has been given more attention is Artificial Neural Network (ANN) despite many pleasing characteristics of ANNs, building a neural network for a particular forecasting problem is a nontrivial task (Ahmad *et al.,* 2014). Modeling issues that affect the performance of an ANN must be considered carefully. One critical decision is to determine the appropriate architecture, that is, the number of layers, the number of nodes in each layer, and the number of arcs which interconnect with the nodes (Keles *et al.*, 2016). Other network design decisions include the selection of activation functions of the hidden and output nodes, the training algorithm, data transformation or normalization methods, training and test sets, and performance measures (Iturriaga *et al.*, 2015). These problems make ANN very tedious to work with and many researchers are now shunning it due to its complications and long process to use.

Moreover, Hidden Markov Model (HMM) is one of the stochastic process used to forecast future events, it is of course one of the best models employed in forecasting but yet it was argued that HMM has many issues that makes it unacceptable by many researchers (Zhu *et al.*, 2017) which include a large number of unstructured parameters, first order HMMs are limited by their first-order markov property (Wang *et al.,* 2018), they cannot express dependencies between hidden states, the HMM is unable to capture higher order correlation (Jiang *et al.,* 2016), only a small fraction of distributions over the space of possible sequences can be represented by a reasonably constrained HMM.

However, the existing models (ARIMA/ARMA, ANN and HMM) discussed above have their respective flaws when it comes to forecasting. Of the models, the best in terms of forecasting as established by many supporting literatures is HMM especially for out-sample forecasting. However, in terms of in-sample forecasting, ANN provides reasonable forecast than ARIMA/ARMA. This drawback motivated and lead us to undertake this research. Thus, in this thesis, the forecast accuracy of HMM is improved by transforming the original series X_t in to $f(X_t) = Y_t$ using ANN-AR. The algorithmic flow involves first modelling X_t using fusion model of ANN-ARIMA then improving HMM with the transformed Y_t.

1.3.1 Research Gap

There have been many researches using HMM, ARMA and ANN such as; Lin, Xiao, and Li, (2020) they forecasted crude oil price volatility via a HM-EGARCH model, Deng, Xiang, Nan, Tian, and Sun, (2019) developed a hybrid model of dynamic time wrapping and hidden Markov model for forecasting and trading in crude oil market, Zhu, Ching, Elliott, Siu, and Zhang, (2017). Developed a Hidden Markov models with threshold effects and their applications to oil price forecasting, Mostafa, and El-Masry, (2016). Conducted a research on oil price forecasting using gene expression programming and artificial neural networks, Kristjanpoller, and Minutolo, (2016) conducted a research on forecasting volatility of oil price using an artificial neural network-GARCH model, Ramyar and Kianfar, (2019) forecasted crude oil prices in which they compared an artificial neural networks and vector autoregressive models, Guo, (2019) conducted a research on oil price forecast using deep learning and ARIMA, Rezaeyan, and Taghizadeh, (2018) Modeled and Forecasted crude oil price with an Autoregressive Integrated Moving Average (ARIMA) Model. All the above models has problems of inaccuracy when using small number of data, this is one of the issues solved by our model in which it is capable of forecasting using small number of data and provide minimum error, similarly, yet there is no research that improved the accuracy of HMM by developing new hybrid HMM using fusion of both ARMA and ANN. This is the main gap that was bridged in this research work.

1.4 Research Questions

The research questions in this study are as follows:

1. How to develop models for time series crude oil price forecasting based on Hidden Markov Model, ARMA Model and Artificial Neural Network?
2. How to develop new hybrid HMM model using fusion of ARMA and ANN to forecast crude oil price?
3. How to evaluate the developed forecasting models based on forecast error evaluation methods?

1.5 Research Objectives

Specifically, the main objectives of this study are:

1. To develop models for time series crude oil price forecasting based on Hidden Markov Model, ARMA Model and Artificial Neural Network.
2. To develop new hybrid HMM model using fusion of ARMA and ANN to forecast crude oil price.
3. To evaluate the developed forecasting models based on forecast error evaluation methods.

1.6 Scope of the Study

This research is based on the development of forecasting models based on Hidden Markov Model, ARMA Model, and Artificial Neural Network as well as new hybrid HMM model using fusion of ARMA and ANN to forecast crude oil prices. Since the oil price volatility is the main concern, the study used daily data. The data were obtained from West Texas Intermediate (WTI) from 2nd January 2014 to 31st December 2018, totaling 1259 days. The data was employed to develop all the four models and the results were evaluated using three different evaluation methods which are Mean Absolute Percentage Error (MAPE), Absolute Error (AE) and Root Mean Square Error (RMSE) to figure out the most accurate forecasting models among the four models developed.

1.7 Significance of the Study

Since crude oil market is highly volatile, the estimation of the time series model must be able to detect its future volatility. This research is of great significance to policy makers, academicians as well as the general public.

To policy makers, this research is of considerable significance in which the research serves as an avenue for the policy makers to make decision as regards to crude oil price. The research provide the future crude oil price that will enable the policy makers to make decision upon.

Similarly, this research play a very vital role to academicians and researchers in which it serves as the reference to those researchers that are interested in this area, it also enhance the knowledge of the researchers by developing new methodology and new hybrid HMM model using fusion of ARMA and ANN. Academicians and researchers will find this research of great significance by exploring more on the models developed in this research.

Additionally, this research is of significance contribution to the general public by highlighting to them on how the crude oil price could be forecasted and it also play a very vital role to the general public by educating them on the effects of crude oil price fluctuation and the advantage of the crude oil price forecasting to the economic growth and development of the world in general.

Overall, we employed Hidden Markov Model, ARMA Model and Artificial Neural Network in forecasting the price volatility of crude oil in this study. We enhanced the applicability of these models by developing new hybrid HMM model using fusion of ARMA and ANN which is more accurate in crude oil price forecasting. The research is of great benefit to the Malaysian government as the crude oil price fluctuation affects Malaysia and many countries in the world, this would immensely contribute to the economic growth and development of Malaysia since crude oil contributes in the economic activities of this nation. The findings of this research if employed by Malaysian government would contribute in budgeting and expenditure analysis with regards to the contribution of crude oil.

1.8 Structure of Thesis

This thesis is structured into six chapters and the content of the chapters are as follows:

Chapter 1: This chapter contains the context of the research introduction, background, questions, objectives, scope, as well as the significance of the research.

Chapter 2: This chapter reviews the literature on the nature and origin of oil, historical analysis of oil, world petroleum industries, dynamics of oil industries, political aspect of oil and many more.

Chapter 3: This chapter presents details of the methodology adopted for this research. Hidden Markov Model, ARMA Model and Artificial Neural Network as well as the new hybrid HMM model properties were explained alongside justification for adopting this approach are outlined.

Chapter 4: This chapter presents the results/findings of data screening analysis. It shows clearly how data screening were conducted to enable the researcher proceeds with the main data analysis and presentations.

Chapter 5: This chapter presents the whole findings of the research, its starts with the result of Hidden Markov Mode followed by results of ARMA model and then the results of Artificial Neural Network and finally the result of new hybrid HMM model. The chapter also contained the error analysis that evaluate the accuracy of each model developed.

Chapter 6: This chapter contains the discussion of the findings of this research, contribution to the body of knowledge (i.e. theoretical contributions, academic contributions as well as contributions to industry). The chapter also presents the research novelty and finally the chapter presents the conclusions of this research work.

1.9 Definition of Key Terms

For the purpose of consistency and to avoid ambiguity, it is necessary to give definition to the key terms used in this research. This is important to ensure that it gives meaning and understanding in the proper context for the study. The terms involved in the importance of this writing include:

Hidden Markov Model: A hidden Markov model is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states.

ARMA Model: ARMA model is a tool for understanding and, perhaps, predicting future values in this series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The AR part involves regressing the variable on its own lagged (i.e. past) values. The MA part involves modeling the error term as a linear combination of error terms occurring contemporaneously and at various times in the past

Artificial Neural Network: An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output.

Crude Oil: Is a naturally occurring, yellow-to-black liquid found in geological formations beneath the Earth's surface which is commonly refined into various types of fuels.

Price: Price is the quantity of payment or compensation given by one party to another in return for goods or services.

Forecasting: This is the process of making prediction of the future based on past and present data and analysis of trends.

1.10 Summary

This chapter has introduced the topic and research objectives that are set to achieved in undertaking of this research. The chapter also contains introduction, background of the research, research problems, and scope of the research as well as structure of thesis. The next chapter presents the reviews of the related literature of this research work with the aim of having a clear focus of the research.

CHAPTER 2

2.1 Introduction

The review of literature is considered a systematic and critical review of the most important published scholarly literature on a particular topic. Scholarly literature refers to published and unpublished data-based literature and conceptual literature materials found in print and non-print forms. This chapter looks at a review of relevant literatures that give a background of the crude oil price forecasting.

2.2 Time Series

Time series modeling is a dynamic research area which has attracted attentions of researchers' community over last few decades. The main aim of time series modeling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series, i.e. to make forecasts. Time series forecasting thus can be termed as the act of predicting the future by understanding the past (Taiwo, Folorunso, and Ogunwobi, 2018). Due to the indispensable importance of time series forecasting in numerous practical fields such as business, economics, finance, science and engineering, etc. (Pradhan, Nayak, and Dhal, 2016), proper care should be taken to fit an adequate model to the underlying time series. It is obvious that a successful time series forecasting depends on an appropriate model fitting. A lot of efforts have been done by researchers over many years for the development of efficient models to improve the forecasting accuracy. As a result, various important time series forecasting models have been evolved in literature.

2.3 Application of Markov Chain in Forecasting

Many researchers worked on the application of markov chain in forecasting such as Saadi, Mustafa, Teller, & Cools, (2016) conducted a research on Forecasting travel behavior using Markov Chains-based approaches, in their research, they propose an integrated approach including Markov Chain Monte Carlo (MCMC) simulation and profiling-based methods to capture the behavioral complexity and the great heterogeneity of agents of the true population through representative micro-samples. The population synthesis method is capable of building the joint distribution of a given population with its corresponding marginal distributions using either full or partial conditional probabilities or both of them simultaneously. The fully probabilistic structure based on Markov Chains characterizing their framework makes it innovative compared to standard activity-based models. Moreover, they used data stemming from the 2010 Belgian Household Daily Travel Survey (BELDAM) to calibrate the modeling framework. They illustrate that this framework effectively captures the behavioral heterogeneity of travelers. Furthermore, they demonstrate that the proposed framework is adequately adapted to meeting the demand for large-scale micro-simulation scenarios of transportation and urban systems.

Kovacs, (2018) investigated the Market Share Modelling and Forecasting Using Markov Chains in the Case of Romanian Banking Institutions, in his research, he attempts to estimate the future market share of Romanian banking institutions using Markov chains method. He used an algorithm to solve a phenomenon based on Markov chains. The results obtained in his research were compared with those reported by the BNR.

AlSkaif, Schram, Litjens, & van Sark, (2017) conducted a research on Smart charging of community storage units using Markov chains, in his paper, a stochastic smart charging framework for CES in residential microgridswas proposed. A linear optimization

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